Artificial Intelligence, Digital Innovation, and Corporate ESG Performance

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ABSTRACT

Using a panel of 732 Chinese listed manufacturing firms from 2011–2022, this paper examines whether firm-level generative artificial intelligence (GAI) capability is associated with improved corporate ESG performance. We construct a text-based GAI measure by counting GAI-related keywords in annual reports and taking ln(count+1), and we measure ESG performance by converting Huazheng ESG ratings into a 1–9 score. Firm- and year-fixed effects results indicate a positive and statistically significant relationship between GAI and ESG outcomes. Mechanism analysis suggests that digital innovation, proxied by firms' digital patents, partially mediates this relationship: GAI is positively related to digital innovation, and digital innovation is positively related to ESG performance. Heterogeneity tests show that the positive association is more evident among state-owned and foreign-invested firms, and it is stronger for large firms. In contrast, the moderating effect of supply chain finance is not statistically supported. A panel threshold model identifies a managerial-efficiency threshold around 6.01×108, below which the GAI–ESG link is insignificant and above which it becomes strongly positive. Robustness checks, including DDML and instrumental-variable estimation, confirm the stability of the main findings.

Keywords: Generative artificial intelligence, Corporate ESG performance, Digital innovation, Manufacturing firms, Managerial efficiency

1. INTRODUCTION

As sustainability disclosure and compliance requirements tighten and stakeholder scrutiny intensifies, ESG has moved beyond a reporting exercise and become an important factor influencing firms' financing conditions, market access, and competitive position. This shift is especially relevant for manufacturing firms. Manufacturing operations are process-driven and involve complex production links and extensive upstream and downstream interactions, which makes ESG management more frequent and more reliant on timely and consistent information across internal functions. As a result, firms face stronger needs for better information integration, clearer internal coordination, and more reliable ESG-related records and disclosures. At the same time, generative AI is increasingly adopted in R&D, process improvement, supply-chain operations, and compliance and risk management. It can help firms process large volumes of information and support decision-making in data-intensive ESG-related tasks [1, 2]. Against this background, it is important to examine whether a higher level of generative AI is associated with better corporate ESG performance, particularly in the manufacturing sector.

Prior research has examined the drivers of corporate ESG performance from multiple levels. At the macro level, institutions and regulation can raise disclosure and compliance requirements and push firms to adjust ESG-related practices, which may improve environmental outcomes but also bring economic trade-offs. Market competition and global supply chain pressure can further strengthen ESG engagement through reputation concerns, customer requirements, and cross-border compliance, and these pressures may be transmitted upstream through supply chain relationships [3, 4, 5]. At the meso level, ESG scrutiny varies systematically across industries because environmental and social externalities are unevenly distributed. Empirical research often treats sectors with higher pollution propensity and stronger regulatory exposure as more ESG salient and frequently studies industries such as pulp and paper, chemicals, oil and gas, metals and mining, and utilities [6]. These examples illustrate that ESG salience is strongly industry-specific. More broadly, the set of ESG issues that are considered financially material also differs by industry, which implies that ESG assessment and stakeholder attention are naturally organized around industry-specific concerns [7]. At the micro level, firm-specific factors also matter. ESG outcomes are linked to strategic orientation, innovation investment, governance arrangements such as board oversight and executive incentives, and the quality of internal control and disclosure, which shape how firms respond to stakeholder demands and manage information asymmetry [8, 9]

Despite these insights, important gaps remain. Existing studies offer rich explanations of ESG outcomes from institutional, industry, and firm perspectives, yet they provide limited evidence on how generative AI becomes embedded within manufacturing firms and how such within-firm implementation translates into ESG improvements. In addition, credible identification of the generative AI–ESG relationship remains challenging because firms with stronger ESG performance may be more willing and able to adopt generative AI, and unobserved managerial capability or organizational quality may affect both. To address these gaps, we focus on manufacturing firms and develop an analysis framework based on the resource-based view and the technology–organization–environment perspective. We measure firm-level generative AI using annual report texts and examine its relationship with ESG performance in a panel setting with fixed effects. We further investigate mechanisms and heterogeneous effects to clarify when and through what channels generative AI contributes to ESG improvements, and we further address endogeneity concerns using an instrumental-variable strategy. We contribute by introducing firm-level generative AI into ESG research, providing manufacturing-based evidence with multiple empirical checks, and offering an integrated framework linking technological capability, organizational conditions, and external environment.

The remainder of this paper is organized as follows. Section 2 presents the theoretical analysis and develops the research hypotheses. Section 3 describes the research design, including data sources, variable construction, and empirical strategy. Section 4 reports the main empirical results. Section 5 discusses the findings and their implications. Section 6 concludes and provides policy suggestions.

2. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

2.1 Direct effect of generative AI on corporate ESG performance

In manufacturing firms, ESG management is increasingly process-based and coordination-intensive. It requires firms to integrate dispersed operational information, align decisions across functions, and implement sustainability practices in a consistent and traceable manner. The resource-based view suggests that persistent performance differences arise from valuable and hard-to-imitate resources and from firms' ability to deploy them effectively [10]. The dynamic capability view further emphasizes that firms must continuously integrate, build, and reconfigure resources to respond to changing external demands and technological conditions [11]. These perspectives are well suited to manufacturing ESG management because effective ESG outcomes depend not only on external pressure, but also on internal capabilities that shape how information is used, how coordination is achieved, and how sustainability goals are translated into routines.

From a resource-based and dynamic capability perspective, generative AI can be viewed as an emerging digital capability that matches these requirements and can therefore influence manufacturing firms' ESG performance. In particular, it aligns with the need to integrate multi-source information, strengthen cross-functional coordination, and support continuous, process-based management. Generative AI can improve the extraction, interpretation, and synthesis of ESG-relevant information, which supports more timely and consistent records and disclosures. It can also facilitate internal coordination by helping different functions interpret requirements, share knowledge, and standardize decision routines around sustainability targets. In addition, generative AI can support monitoring and compliance work that relies heavily on documents and reporting, which strengthens managerial oversight and reduces compliance-related risks. It can further enable iterative problem solving in R&D and operations, which supports process upgrading and operational improvement and may translate into better resource efficiency and more stable implementation of ESG practices. Based on this reasoning, we propose the following hypothesis.

H1. Firms with a higher level of generative AI exhibit better overall ESG performance.

2.2 Mechanisms of influence

2.2.1 Digital innovation as a linking mechanism

Digital innovation provides a natural bridge between generative AI and ESG performance because it reflects a firm's dynamic capability to reconfigure digital resources, and it is closely related to both the adoption of generative AI and the improvement of ESG outcomes. Generative AI can promote digital innovation by lowering the cost of knowledge search and recombination, accelerating idea generation and experimentation in R&D and operations, and supporting the development of new digital solutions and digitally enabled processes. In manufacturing firms, these effects are reinforced by the data-intensive nature of production and supply-chain management, where generative AI can help transform dispersed information into usable inputs for innovation activities. In turn, stronger digital innovation can improve ESG performance through several pathways. It can support cleaner and more efficient production by enabling process optimization and resource-saving technologies. It can also strengthen monitoring and risk control by improving data collection, traceability, and internal control systems, which reduces compliance risk and improves disclosure quality. Moreover, digital innovation can facilitate more transparent and responsive stakeholder communication by improving reporting systems and the reliability of ESG-related information. Based on this logic, we expect that,

H2a: Generative AI improves corporate ESG performance partly by enhancing firms' digital innovation.

2.2.2 The moderating role of supply chain finance

Generative AI can improve corporate ESG performance on average, but the magnitude of this effect depends on whether firms can bear the sizable upfront costs and the relatively long payback period of AI deployment. When financing constraints are tight, firms are more likely to prioritize short-term operations and liquidity buffers, which weakens the translation of generative AI use into tangible ESG outcomes such as energy efficiency improvement, compliance work, and governance upgrading. Supply chain finance offers a relevant financing arrangement in this context. It builds financing capacity on the credit of core firms and on transaction-based assets such as accounts receivable and verified orders, thereby improving liquidity and lowering funding costs for upstream and downstream firms in the supply chain [12].

From the resource-based view and the dynamic capabilities perspective, the value of a general-purpose technology is typically realized through complementary investments and organizational change. Evidence on information technology shows that performance gains require coherent bundles of technology, organizational practices, and process redesign rather than stand-alone adoption [13, 14, 15]. In a similar spirit, generative AI is more likely to become a sustained capability when firms can match it with complementary resources, including capital investment for computing and data infrastructure, data governance to ensure data quality and auditability, and process reengineering to embed AI into operational control and disclosure routines [16]. Supply chain finance can strengthen this matching in two ways. First, by easing financing constraints, it enables firms to fund the complementary investments needed for integrating generative AI into ESG-related routines. Second, because supply chain finance relies on verifiable transaction data and typically increases external scrutiny from core firms and financiers, it can improve the credibility and enforceability of ESG-relevant information and practices, which helps convert AI-enabled monitoring and reporting into governance discipline and measurable ESG improvement [17, 18].

Based on this reasoning, we propose the following hypothesis.

H2b: Supply chain finance positively moderates the relationship between generative AI and corporate ESG performance.

2.3 Heterogeneity effects

The marginal effect of generative AI on ESG performance is not automatic. It depends on whether firms possess complementary resources that can convert AI inputs into ESG governance capability, and whether they face sufficiently strong external constraints that motivate them to apply AI toward sustainability goals rather than only short-term efficiency gains.

First, the effect may differ across ownership types. Compared with private firms, state-owned enterprises typically have more stable access to finance and resources, which helps them bear the fixed costs associated with deploying generative AI and embedding it into governance routines. They also tend to face stronger mandates related to public objectives, which encourages them to use AI for emissions monitoring, compliance reporting, and supply-chain governance, leading to a stronger ESG-enhancing effect [19]. Foreign-invested firms are often more deeply integrated into global value chains and face stronger scrutiny from international investors and regulators. As a result, they are more likely to deploy AI in green production, employee protection, and supply-chain due diligence, and to translate AI-enabled transparency into ESG improvement through external monitoring mechanisms [20]. In contrast, private firms are more likely to be constrained by financing conditions, data foundations, and talent shortages, and their ESG responses may be more selective. Their AI investments may therefore be directed toward near-term operational gains rather than systematic ESG upgrading [21]. Based on this reasoning, we propose the following hypothesis.

H3a. The positive effect of generative AI on ESG performance is stronger for state-owned and foreign-invested firms than for other firms.

Second, firm size can shape whether generative AI can be transformed into ESG performance gains. The implementation of generative AI usually involves substantial fixed investment and learning costs, including computing resources, data infrastructure, and cross-functional process redesign. Large firms tend to have stronger capital capacity, richer data assets, and more mature internal control systems, which makes it easier to build the organizational complements needed to embed generative AI into ESG-related routines and achieve larger ESG benefits in areas such as energy saving, safety management, compliance, and disclosure [22]. Large firms also have higher public visibility and face stronger reputational and legitimacy pressure, which increases the incentive to use AI for verifiable and traceable ESG governance rather than for efficiency improvements alone [23]. By contrast, small and medium-sized firms may be more constrained by financing and talent and may lack the data and governance foundations needed to complete the transformation from AI investment to systematic ESG improvement in the short run [24]. Therefore, we propose the following hypothesis.

H3b. The positive effect of generative AI on ESG performance is stronger for large firms than for small firms.

2.4 Threshold effect of managerial efficiency

Generative AI typically requires complementary investments such as data governance, process redesign, and cross-functional coordination. When managerial efficiency is insufficient, AI adoption is more likely to remain at a pilot stage or become symbolic, and it is difficult to embed AI into key governance routines such as emissions monitoring, compliance disclosure, and internal control. In this case, ESG improvement may be weak, or even offset by implementation frictions [25, 11]. At the same time, theory does not necessarily imply a clear threshold. On the one hand, cloud services and standardized AI tools can lower fixed costs, which allows firms with different managerial capabilities to obtain AI-related benefits in a more incremental manner [26]. On the other hand, improvements in ESG governance often accumulate gradually, and the performance response may not exhibit a sharp break at a specific point [27]. Taken together, these arguments suggest that managerial efficiency may act as a threshold condition that shapes whether generative AI can be converted into measurable ESG gains. We therefore test whether the effect of generative AI on ESG performance differs across regimes defined by managerial efficiency and propose the following hypothesis.

H4. The effect of generative AI on ESG performance exhibits a significant threshold effect with respect to managerial efficiency.

3. RESEARCH DESIGN

3.1 Variable construction

3.1.1 Dependent variable

The dependent variable is the firm-year average ESG score for firm *i* in year *t*. We operationalize ESG performance using the Huazheng ESG rating system. This system includes nine rating levels, namely C, CC, CCC, B, BB, BBB, A, AA, and AAA. We convert these categories into a numerical scale from 1 to 9, where 1 corresponds to the lowest rating (C) and 9 corresponds to the highest rating (AAA). Based on this conversion, we compute the ESG score for each listed firm in each year and denote it as ESG_{it} . A higher value indicates better ESG performance.

3.1.2 Key explanatory variable

The key explanatory variable measures a firm's generative AI level. We first collect annual reports for all sample firms and convert the documents into plain text. We then construct a keyword dictionary to capture generative AI content in annual reports. The construction proceeds as follows. We use three dimensions as the seed-word search scope, including a foundation layer, a technology layer, and a model-ecosystem layer. We use major industry white papers as a corpus, including the 2022 China Large Model Development White Paper, the AIGC White Paper, the AI Large Model Development White Paper, and the China AI Large Model Technology White Paper (2023). Based on these sources, we extract relevant contexts from annual reports and identify high-frequency word combinations. We then supplement the keywords based on prior studies and apply expert validation to ensure relevance and consistency with core characteristics of generative AI. Finally, using Python, we tokenize annual report texts, extract generative AI keywords, and count the occurrences of these feature words. We add one to the count and take the natural logarithm to obtain AI_{it} .

3.1.3 Control variables

To mitigate omitted-variable bias, we control for a set of firm-level and region-level characteristics X_{it} that are commonly related to ESG performance and technology adoption. The controls include, but are not limited to, accounts payable turnover, leverage, EBIT margin, return on equity, the logarithm of net fixed assets, and a group of dummy variables capturing the firm's salary disclosure method.

3.1.4 Mechanism variable

To test the mechanism through which generative AI affects ESG performance, we use digital innovation as the mediator. We proxy digital innovation using the number of digital patents of listed firms.

3.1.5 Moderating variable

For moderation analysis, we introduce a firm-year supply chain finance index. We measure supply chain finance using keyword-frequency counts of supply chain finance terms in annual reports and apply a logarithmic transformation.

3.1.6 Threshold variable

We use firms' annual management expenses to measure managerial efficiency.

3.2 Empirical models

3.2.1 Baseline model: fixed effects specification

We estimate a firm and year fixed effects model to identify the relationship between generative AI and ESG performance.

$$ESG_{it} = \alpha + \beta AI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Equation (1), ESG_{it} denotes the firm-year ESG score, AI_{it} is the generative AI level, and X_{it} is the vector of control variables. μ_i and λ_t denote firm fixed effects and year fixed effects, respectively, which absorb time-invariant firm characteristics and common year shocks. ε_{it} is the error term. We cluster standard errors at the firm level to address within-firm correlation and serial correlation. Under this specification, we evaluate the net effect of generative AI on ESG performance conditional on observables, firm heterogeneity, and year shocks. This baseline framework is also used to ensure consistency across subsequent mechanism, moderation, and threshold analyses.

3.2.2 Mechanism model: mediation tests

The baseline regression reveals whether generative AI is associated with ESG performance, but it does not explain why. To identify the transmission path, we use firms' digital innovation as the mechanism variable and estimate mediation regressions.

$$DT_{it} = \alpha_1 + \delta AI_{it} + \theta X_{it} + \mu_i + \lambda_t + u_{it} \tag{2}$$

$$ESG_{it} = \alpha_2 + \phi DT_{it} + \gamma X_{it} + \mu_i + \lambda_t + v_{it} \tag{3}$$

Equation (2) estimates the relationship between generative AI and digital innovation. Equation (3) evaluates whether digital innovation is associated with ESG performance, conditional on controls and fixed effects. Together with the baseline regression, these models provide evidence on the mediation channel.

3.2.3 Moderation model

After establishing the overall effect of generative AI on ESG performance, we further examine whether the relationship is context dependent. To test whether supply chain finance moderates the generative AI–ESG relationship, we augment the baseline model with an interaction term between generative AI and supply chain finance.

$$ESG_{it} = \alpha + \eta (AI_{it} \times SCF_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

In this model, SCF_{it} denotes the firm *i* year *t* supply chain finance measure. The coefficient η on the interaction term captures the moderating effect. If $\eta > 0$, SCF_{it} exerts a positive moderating effect; otherwise, it has a negative moderating effect. Other variables are defined consistently with Equation (1).

3.2.4 Threshold model

To capture possible nonlinear effects, we test whether managerial efficiency serves as a threshold condition in the generative AI–ESG relationship. We follow Hansen's panel threshold framework [28] and estimate a single-threshold model.

$$ESG_{it} = \alpha + \beta_L AI_{it} I(ME_{it} \leq \alpha) + \beta_H AI_{it} I(ME_{it} > \alpha) + \rho DT_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where denotes the annual average ESG score of firm i in year t, represents the level of generative artificial intelligence, and is the annual management expenses. Let αbe the endogenously estimated threshold value of managerial efficiency, and $I(\cdot)$ be the indicator function. The coefficients β_L and β_H characterize the marginal effect of AI on ESG when managerial efficiency is below or above the threshold, respectively. DT_{it} denotes the level of digital innovation, and its coefficient ρ captures the linear effect of DT on ESG. X_{it} is a vector of other control variables. μ_i and λ_t denote firm and year fixed effects, respectively, and ε_{it} is the stochastic disturbance term. By comparing the magnitude and statistical significance of β_L and β_H, we can test whether a managerial-efficiency threshold effect exists.

3.3 Data and sample

We set the sample period to 2011–2022. This is motivated by the view that, after 2011, AI increasingly moved from laboratory research toward broader industrial applications and began to reshape production and management practices. The data mainly come from the Wind database and firms' publicly available annual reports. For missing variables, we apply linear interpolation and drop firms with substantial missing data. The final sample includes 732 listed firms. To unify data scales, we take the natural logarithm of net fixed assets.

4. EMPIRICAL ANALYSIS

4.1 Baseline results

We estimate Equation (1) to examine the relationship between generative AI and corporate ESG performance. The regression results are reported in Table 1.

Table 1: Baseline Regression Results of Generative AI on ESG Performance

	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e
Generative AI level	0.0803**	0.0804**	0.0800**	0.0807**	0.0803**	0.0815**
	(2.05)	(2.05)	(2.04)	(2.06)	(2.05)	(2.09)
Accounts payable turnover ratio	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(3.56)	(3.58)	(3.57)	(3.57)	(3.56)	(3.48)
EBIT margin	0.0061***		0.0057***	0.0061***	0.0061***	0.0059***
	(2.75)		(2.59)	(2.76)	(2.75)	(2.68)
ROE (A)	-0.0048***			-0.0048***	-0.0048***	-0.0035**
	(-3.08)			(-3.08)	(-3.08)	(-2.22)
leverage ratio	-0.0933***	-0.1081***	-0.1054***	-0.0928***	-0.0933***	-0.1168***
	(-3.32)	(-3.89)	(-3.79)	(-3.30)	(-3.32)	(-4.12)
Annual salary disclosure method	-0.0858**				-0.0858**	-0.0827**
	(-2.25)				(-2.25)	(-2.18)
Log of net fixed assets						0.0575***
						(6.20)
_cons	4.1658***	4.0945***	4.0972***	4.0760***	4.1658***	2.9605***
	(35.20)	(36.77)	(36.81)	(36.57)	(35.20)	(13.01)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8784	8784	8784	8784	8784	8783
r^2_w	0.0197	0.0171	0.0179	0.0190	0.0197	0.0244

t statistics in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Across specifications with gradually added controls, the coefficient on AI_{it} remains positive and is significant at least at the 5 percent level. This indicates that higher generative AI levels are associated with better ESG performance. In terms of economic magnitude, using Column (6) as a reference, the coefficient on generative AI is 0.0815 and is significant at the 5 percent level. This implies that a higher generative AI level is associated with an improvement of approximately 8.2 percent in firms' ESG performance. These results support H1.

4.2 Heterogeneity analysis

We further examine heterogeneity along two dimensions, namely firm ownership type and firm size. The results are reported in Table 2 and Table 3.

Table 2: Heterogeneity Analysis by Firm Ownership Type

	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e	Average annual ESG score_e
Generative AI level	0.1201*	0.0401	0.9296*	-0.2790
	(1.86)	(0.79)	(2.52)	(-0.25)
leverage ratio	-0.2130**	-0.0656**	-0.1947	0.6119
	(-2.37)	(-2.08)	(-0.43)	(0.77)
Accounts payable turnover ratio	0.0001**	-0.0000	-0.0004	-0.0001
	(2.15)	(-0.49)	(-0.59)	(-1.52)
EBIT margin	-0.0098	0.0058***	0.2402*	0.0680
	(-0.50)	(2.58)	(1.85)	(1.26)
ROE (A)	0.0093*	-0.0065***	-0.0528*	0.1755*
	(1.82)	(-3.65)	(-1.74)	(2.13)
Annual salary disclosure method	-0.1117**	-0.0288	0.0000	0.0818
	(-2.49)	(-0.39)	(.)	(0.33)
Log of net fixed assets	0.0382***	0.0665***	0.0827	0.2138**
	(2.65)	(4.37)	(1.39)	(2.33)
_cons	3.5231***	2.5054***	-620.0000	-0.6395
	(10.61)	(6.80)	(-0.38)	(-0.36)
City FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	4919	3378	252	149

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 2 shows that, for state-owned enterprises, the coefficient on generative AI is 0.1201 with a t-statistic of 1.86 and is significant at the 10 percent level. This suggests that, within state-owned enterprises, higher generative AI levels are associated with higher ESG scores. For private firms, the coefficient is 0.0401 with a t-statistic of 0.79 and is not statistically significant. For foreign-invested firms, the coefficient is 0.9296 with a t-statistic of 2.52 and is significant at the 5 percent level, indicating a stronger positive association. For other firm types, the coefficient is negative and not significant. Overall, the positive effect of generative AI on ESG performance is concentrated among state-owned and foreign-invested firms. This supports H3a.

Table 3: Heterogeneity Analysis by Firm Size

	Average annual ESG score_e	Average annual ESG score_e
Generative AI level	-0.0138	0.1365**
	(-0.25)	(2.38)
leverage ratio	-0.0932***	-0.3192***
	(-3.15)	(-2.68)
Accounts payable turnover ratio	0.0000***	-0.0007
	(3.63)	(-0.58)
EBIT margin	-0.0003	0.0067***
	(-0.03)	(2.88)
ROE (A)	-0.0038**	0.0283***
	(-2.09)	(4.34)
Annual salary disclosure method	-0.0951*	-0.0767
	(-1.95)	(-1.27)
Log of net fixed assets	0.0434***	0.0355*
	(3.24)	(1.79)
_cons	2.7492***	3.8538***
	(6.46)	(8.61)
City FE	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	4919	3378
R^2	0.0248	0.0396

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 3 shows that, for small firms, the coefficient on generative AI is −0.0138 and is not statistically significant. For large firms, the coefficient is 0.1365 with a t-statistic of 2.38 and is significant at the 5 percent level. This indicates that the ESG-enhancing effect of generative AI is more evident among large firms. This supports H3b.

4.3 Mechanism analysis

To test whether generative AI affects ESG performance through digital innovation, we estimate Equations (2) and (3). The results are reported in Table 4.

Table 4: Mechanism Analysis: The Mediating Role of Digital Innovation

	Average annual ESG score_e	DT1	Average annual ESG score_e
Generative AI level	0.0809**	0.2120***	
	(2.07)	(5.49)	
leverage ratio	-0.1186***	0.0170	-0.1191***
	(-4.24)	(0.62)	(-4.26)
Accounts payable turnover ratio	0.0000***	0.0000***	0.0000***
	(3.48)	(-1.14)	(3.53)
EBIT margin	0.0059***	-0.0038*	0.0061***
	(2.68)	(-1.73)	(2.77)
ROE (A)	-0.0034**	0.0008	-0.0035**
	(-2.18)	(0.51)	(-2.19)
Annual salary disclosure method	-0.0818**	-0.0010	-0.0821**
	(-2.15)	(-0.03)	(-2.16)
Log of net fixed assets	0.0586***	0.0539***	0.0559***
	(6.36)	(5.92)	(6.06)
DT1			0.0473***
			(4.20)
City FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	8804	8804	8804
R^2	0.0242	0.0246	0.0258

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Column (2) shows that, when digital innovation is the dependent variable, the coefficient on generative AI is 0.2121 and is significant at the 1 percent level. This suggests that higher generative AI levels are associated with higher digital innovation. Column (3) uses ESG performance as the dependent variable and includes the digital innovation measure. The coefficient on digital innovation is 0.0473 and is significant at the 1 percent level. These results indicate that generative AI improves ESG performance partly by promoting digital innovation, supporting H2a.

To test whether supply chain finance moderates the effect of generative AI on ESG performance, we add the interaction term between generative AI and supply chain finance to the baseline model. The results are reported in Table 5.

Table 5: Moderation Analysis: The Role of Supply Chain Finance

	Average annual ESG score_e
tj	0.000192
	(1.53)
leverage ratio	-0.3153***
	(-6.34)
Accounts payable turnover ratio	0.000045**
	(2.46)
EBIT margin	0.000579
	(0.06)
ROE (A)	-0.000576
	(-0.24)
Annual salary disclosure method	-0.0870**
	(-2.30)
Log of net fixed assets	0.0660***
	(6.51)
City FE	Yes
Firm FE	Yes
Year FE	Yes
N	8620
R^2（within）	0.0250

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

In Column (1), the coefficient on the interaction term is 0.00019 with a t-statistic of 1.53 and is not significant at the 10 percent level. This suggests that the interaction between supply chain finance and generative AI does not have a statistically significant effect on ESG performance. The overall model F-test is significant, indicating that the model has explanatory power. Therefore, H2b is not supported by the data.

4.4 Threshold effect

We test whether the effect of generative AI on ESG performance exhibits a managerial-efficiency threshold. We estimate the panel threshold model and report results in Table 6 and Table 7.

Table 6: Threshold Estimator for Managerial Efficiency

Threshold estimator (level = 95):

model	Threshold	Lower	Upper
Th-1	6.01×10^8	5.33×10^8	6.20×10^8

Threshold effect test (bootstrap = 50):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	3198.5802	0.3646	17.03	0.0000	11.4413	14.3364	14.3895

Table 7: Panel Threshold Model Regression Results

Generative AI level	Average annual ESG score_e
0	-0.0136
	(-0.32)
1	0.3668***
	(4.23)
N	8784
R^2（within）	0.0091

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

The threshold estimation indicates a significant single threshold for managerial efficiency, with an estimated threshold value of approximately 6.01×10^8. The threshold-effect F statistic is 17.03 with a p-value of 0.000, which rejects the null hypothesis of no threshold effect. This implies that the relationship between generative AI and ESG performance differs across managerial-efficiency regimes.

When managerial efficiency is below the threshold, the coefficient on generative AI is −0.0138 with a t-statistic of −0.32 and is not statistically significant. This suggests that, among firms with lower managerial efficiency, generative AI does not significantly improve ESG performance. The technology may remain at a symbolic or experimental stage and may not be effectively converted into measurable ESG gains. In contrast, when managerial efficiency is above the threshold, the coefficient on generative AI becomes 0.3668 with a t-statistic of 4.23 and is significant at the 1 percent level. This indicates that generative AI can generate substantial ESG benefits only after firms reach a certain level of internal managerial efficiency.

4.5 DDML

To test robustness with respect to functional form and to reduce potential biases induced by linear specifications, we apply a double machine learning (DDML) approach and re-estimate the marginal effect of generative AI on ESG performance. The results are reported in Table 8.

Table 8: Robustness Check: Double Machine Learning (DDML) Estimation

	Average annual ESG score_e
Generative AI level	0.142**
	(2.98)
_cons	-0.00773
	(-1.06)
N	8804

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

The estimated coefficient on generative AI is 0.142 with a t-statistic of 2.98 and is significant at the 5 percent level. This suggests that the positive relationship between generative AI and ESG performance remains robust when allowing controls to affect ESG in a highly nonlinear way and using machine learning procedures to partial out covariate effects.

4.6 Additional robustness tests

We conduct winsorization to address potential influences of extreme values. Specifically, we replace the top and bottom 1 percent of observations with their corresponding percentile values. The results are reported in Table 9.

Table 9: Additional Robustness Test: Winsorization

	Average annual ESG score_e
Generative AI level	0.0809**
	(2.07)
leverage ratio	-0.1186***
	(-4.24)
Accounts payable turnover ratio	0.0000413***
	(3.48)
EBIT margin	0.00591***
	(2.68)
ROE (A)	-0.00344**
	(-2.18)
Annual salary disclosure method	-0.0818**
	(-2.15)
Log of net fixed assets	0.0586***
	(6.36)
City FE	Yes
Firm FE	Yes
Year FE	Yes
N	8804
R^2（within）	0.0242

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

The coefficient on generative AI remains positive and significant at the 5 percent level, with a value of 0.0809 and a t-statistic of 2.07. The sign and magnitude are close to the baseline estimates, indicating that the main results are robust to outliers.

We also control for macro policy interventions such as “intelligent manufacturing pilot” programs by adding a policy variable to the baseline model. The results are reported in Table 10.

Table 10: Additional Robustness Test: Controlling for Macro Policy Interventions

	Average annual ESG score_e
Generative AI level	0.7618*
	(1.95)
DID	0.3463***
	(4.89)
leverage ratio	-0.1191***
	(-4.27)
Accounts payable turnover ratio	0.0000416***
	(3.51)
EBIT margin	0.00585***
	(2.66)
ROE (A)	-0.00351**
	(-2.23)
Annual salary disclosure method	-0.0751**
	(-1.98)
Log of net fixed assets	0.0572***
	(6.22)
City FE	Yes
Firm FE	Yes
Year FE	Yes
N	8804
R^2（within）	0.0271

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

After including the DID-style policy control, the coefficient on generative AI remains positive and is significant at the 10 percent level. This suggests that the ESG-enhancing effect of generative AI is not driven by specific policy contexts.

Finally, to mitigate concerns about reverse causality and omitted variables, we conduct an endogeneity test using two-stage least squares (2SLS). In the first stage, we use executive incentives as an instrumental variable and regress generative AI on the total compensation of the top three executives (TOP3ManageSumSalary_57) and control variables. The first-stage results are reported in Table 11.

Table 11: Endogeneity Test: First-Stage Regression Results

First- stage regressions

	Generative AI level
TOP3ManageSumSalary_57_e	2.65×10^{-9}
	(3.68)***

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

The instrumental variable has a positive and statistically significant coefficient, suggesting that relevance is satisfied. The second-stage regression results are reported in Table 12.

Table 12: Endogeneity Test: Second-Stage (2SLS) Regression Results

Instrumental variables (2SLS) regression

	Average annual ESG score_e
Generative AI level	15.1892
	(3.58)***

t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

In the second stage, the coefficient on the instrumented generative AI variable is positive and significant at the 1 percent level. This indicates that, after accounting for potential endogeneity, generative AI remains positively associated with ESG performance and the baseline conclusion is robust under the instrumental-variable setting.

5. DISCUSSION

This paper investigates how firm-level generative AI capability relates to ESG performance in manufacturing firms. The results point to a positive and robust association between generative AI and ESG outcomes, while also showing that the benefits are uneven and depend on organizational conditions. In particular, digital innovation appears to be an important transmission channel, the effect is stronger for state-owned and foreign-invested firms and for larger firms, and a clear managerial-efficiency threshold separates firms that can translate generative AI into measurable ESG gains from those that cannot. By contrast, the expected positive moderating role of supply chain finance is not strongly supported.

These patterns are consistent with how ESG management operates in manufacturing. Manufacturing ESG is not only a disclosure task. It is closely tied to routine operational control, traceability, and cross-functional execution. In practice, generative AI is most likely to matter when it is embedded into data-intensive workflows such as energy and emissions data reconciliation, anomaly detection in production and safety records, supplier documentation review, and the drafting and verification of compliance materials. Firms that deploy large-model tools as internal assistants for reporting, audit preparation, and policy interpretation can reduce the cost of documentation work and improve consistency. Firms that combine generative AI with production data systems can also support continuous improvement by turning dispersed information into operational signals. To strengthen the link to firm practice, this section can be complemented with a small set of verifiable manufacturing cases drawn from corporate sustainability reports or industry reports, describing which specific tools were used, where they were implemented, and what measurable ESG-related outcomes were reported.

Relative to the ESG literature that emphasizes institutional constraints, industry salience, and governance structures, this study highlights a technology-enabled, within-firm pathway. It complements research on digitalization and sustainability by focusing on generative AI as a distinct capability rather than a broad digital investment proxy. It also differs from work on AI and firm performance that mainly centers on productivity or innovation outcomes. Our evidence suggests that the ESG value of generative AI is best understood as a capability problem. The key issue is whether firms can convert generative AI from a tool into a repeatable organizational routine that improves monitoring, coordination, and control in sustainability-related activities.

The mediation results support this interpretation. Digital innovation captures the firm’s ability to reconfigure digital resources and turn technological inputs into scalable solutions. When generative AI strengthens digital innovation, the firm is more likely to upgrade processes, improve traceability, and enhance internal control and reporting systems. These changes are closely aligned with ESG improvement in manufacturing, where operational performance and governance processes are tightly coupled. The mechanism evidence therefore helps clarify why the main effect is not merely a reporting artifact. It indicates that generative AI is associated with changes that are consistent with substantive capability building.

The heterogeneity and threshold findings further sharpen the capability-based explanation. The stronger effects for state-owned and foreign-invested firms and for larger firms are consistent with differences in complementary resources and external constraints. These firms typically have stronger data foundations, more formalized control systems, and higher scrutiny from regulators, investors, and global supply chain partners. They are therefore more likely to allocate generative AI to ESG-relevant routines rather than limiting its use to narrow efficiency gains. The managerial-efficiency threshold provides a clear boundary condition. When managerial efficiency is low, adoption may remain fragmented, experimental, or symbolic, and implementation frictions can offset potential benefits. Once managerial efficiency exceeds a critical level, firms are better able to integrate data governance, redesign processes, and coordinate across functions, which makes it more likely that generative AI becomes embedded in emissions monitoring, compliance disclosure, and internal control routines. This interpretation connects the empirical threshold directly to the dynamic capability logic.

The lack of strong support for supply chain finance as a moderator is also informative. One possibility is that supply chain finance mainly addresses short-term liquidity, while the ESG payoff from generative AI depends more on organizational readiness and process redesign. Another possibility is that the text-based supply chain finance measure reflects attention or disclosure rather than effective financing capacity. More broadly, the result suggests that financing is only one complement and may not be the binding constraint once managerial efficiency and execution capability are accounted for.

Several implications follow. For managers, the findings suggest that ESG returns from generative AI are more likely when firms invest in data governance and redesign ESG-related workflows so that AI outputs are auditable and actionable. For policymakers, encouraging adoption alone may be insufficient. Programs that support managerial upgrading, standard-setting for data quality, and diffusion of digital innovation capabilities may yield larger ESG benefits, especially for smaller firms. Future research can improve measurement of generative AI capability beyond annual-report texts, link generative AI more directly to operational ESG outcomes, and use stronger quasi-experimental designs to further address identification challenges.

6. CONCLUSIONS, POLICY IMPLICATIONS, AND LIMITATIONS

6.1 Conclusion

This paper examines whether a higher level of generative AI is associated with better ESG performance among Chinese listed manufacturing firms over 2011–2022 (final sample: 732 firms). Using a fixed-effects framework, we find a robust positive relationship between firm-level generative AI and ESG performance. In the preferred specification, the coefficient on generative AI is positive and statistically significant.

We further explore mechanisms and boundary conditions. The mediation analysis indicates that generative AI is positively associated with digital innovation, and digital innovation is positively associated with ESG performance, supporting the channel that generative AI improves ESG partly through promoting digital innovation. The heterogeneity analysis shows that the positive association is concentrated among state-owned enterprises and foreign-invested firms, while it is not statistically significant for private firms, and the effect is stronger for large firms.

Regarding nonlinearity, the threshold test identifies a significant single threshold in managerial efficiency. Below the threshold, the generative AI coefficient is negative and insignificant, whereas above the threshold it becomes strongly positive and significant, indicating that ESG gains from generative AI materialize mainly when managerial efficiency is sufficiently high. Several robustness checks, including DDML, confirm the stability of the main conclusion.

6.2 Policy implications

The results suggest that generative AI should be treated as an organizational capability rather than a stand-alone tool for ESG improvement. Since ESG benefits are concentrated in the high managerial-efficiency regime, firms should prioritize complementary investments that enable embedding AI into auditable governance and operational routines, including data governance, process redesign, and cross-functional coordination. The mediation evidence implies that aligning generative AI adoption with digital innovation activities can increase the likelihood of ESG gains. For policymakers, differentiated support may be more effective than uniform adoption incentives, given the stronger effects among state-owned and foreign-invested firms and among large firms. Finally, supply chain finance does not significantly strengthen the generative AI–

ESG link in our tests, suggesting that financing arrangements alone may be insufficient without capability-building complements.

6.3 Limitations

First, the generative AI and supply chain finance measures are constructed from annual-report texts and may partly reflect disclosure intensity rather than implementation depth. Second, although we employ multiple robustness checks and an IV design, endogeneity concerns cannot be fully eliminated in an observational setting. Third, ESG is measured using an aggregate rating score, and future work may examine pillar-level effects and alternative ESG providers. Finally, extending the analysis beyond manufacturing and beyond a single institutional context would help assess external validity.

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